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FULL LENGTH ARTICLE

Determination of efficient and inefficient units for watermelon production-a case study: Guilan province of Iran

Ashkan Nabavi-Pelesaraei [a,b,*], **Reza Abdi** [c], **Shahin Rafiee** [a], **Iraj Bagheri** [d]

[a] Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran
[b] Young Researchers and Elite Club, Langroud Branch, Islamic Azad University, Langroud, Iran
[c] Department of Agricultural Machinery Engineering, Faculty of Agriculture, University of Tabriz, Tabriz, Iran
[d] Department of Agricultural Mechanization Engineering, Faculty of Agricultural Sciences, University of Guilan, Rasht, Iran

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Abstract In this study, data envelopment analysis (DEA) approach was utilized for optimizing required energy and comparing greenhouse gas (GHG) emissions between efficient and inefficient units for watermelon production in Guilan province of Iran. For this purpose, two models including constant returns to scale (CCR) and variable returns to scale (BCC) were applied to determine efficiency scores for watermelon producers. Based on the results, the average of technical, pure technical and scale efficiency was computed as 0.867, 0.957 and 0.906, respectively. Also, 36 and 71 watermelon producers were efficient based on CCR and BCC models, respectively. The total optimum energy required and energy saving were calculated as 34228.21 and 6000.77 MJ ha^{-1}, respectively. Moreover, the highest percentage of energy saving belonged to the chemical fertilizers with 76.62%. The energy use efficiency of optimum units was determined as 1.52 and this rate increased about 18% when compared with existing farms. Also, the energy forms including direct, indirect, renewable and non-renewable energy improved about 15%, 15%, 10% and 15%, respectively. Furthermore, total GHG emissions of efficient and inefficient farms were found to be about 869 and 1239 $kgCO_{2eq.}$ ha^{-1}, respectively. Biocides had the highest difference of GHG emissions between efficient and inefficient farms. Finally, it can be said that applying the DEA approach can reduce

* Corresponding author at: Young Researchers and Elite Club, Langroud Branch, Islamic Azad University, Langroud, Iran. Tel.: +98 9127155205.
E-mail addresses: ashkan.nabavi@yahoo.com, ashkan.nabavi@ut.ac.ir (A. Nabavi-Pelesaraei).

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total GHG emissions about 371 $kgCO_{2eq.}$ ha^{-1} for watermelon production in the studied region.

1. Introduction

Energy use in agriculture has developed in response to increasing populations, limited supply of arable land and desire for an increasing standard of living. In all societies, these factors have encouraged an increase in energy inputs to maximize yields, minimize labor-intensive practices, or both (Esengun et al., 2007). In the developed countries, an increase in the crop yield was mainly due to an increase in the commercial energy inputs in addition to improved crop varieties (Banaeian et al., 2010). Watermelon (*Citrullus lanatus*) is a member of the cucurbit family (*Cucurbitaceae*). The crop is grown commercially in areas with long frost-free warm periods (Prohens and Nuez, 2008).Watermelon is utilized for the production of juices, nectars, fruit cocktails, etc (Wani et al., 2008). Data envelopment analysis (DEA) is a non-parametric technique of frontier estimation which has been used and continues to be used extensively in many settings for measuring the efficiency and benchmarking of decision making units (DMUs) (Mobtaker et al., 2012). In addition, DEA is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the empirical observations. DEA models are broadly divided into two categories on the basis of orientation: input-oriented and output-oriented (Omid et al., 2011). On the other hand, as energy inputs in agriculture rapidly increased and accrued several benefits to farmers, these also adversely influenced the environment (Soni et al., 2013). Carbon dioxide is the main contributor to greenhouse gases (GHG) released into the atmosphere and there is a significant correlation between agricultural production, energy use and CO_2 emissions. Notwithstanding these factors, GHGs would change current environmental circumstances and these changes will have uncontrolled effects on the agricultural sector. The contribution of global agriculture to air pollution through the consumption of energy is small, accounting for about 5–13.5% of annual GHG emissions (Safa and Samarasinghe, 2012). The energy consumption reduction is considered as the main solution for reduction of GHG emissions in agriculture activity. This shows the importance of energy optimization effects on improving the environmental situation. In recent years, several authors have applied DEA for both energy optimization and GHG emissions reduction. Khoshnevisan et al. (2013) applied the DEA approach to optimization of energy required and GHG reduction for cucumber production in Isfahan province of Iran. In another study, the energy inputs for rice were optimized by the DEA approach. Then, the GHG emissions were determined for the present and target units (Nabavi-Pelesaraei et al., 2014b). Moreover, the energy use of orange production was optimized using the non-parametric method of DEA. After determining efficient and inefficient units, the GHG emissions were calculated for both of units (Nabavi-Pelesaraei et al., 2014a).

This paper presents an application of DEA to differentiate efficient and inefficient watermelon producers in Guilan Province of Iran, pinpoint the best operating practices of energy usage, recognize wasteful uses of energy inputs by inefficient farmers and suggest necessary quantities of different inputs to be used by each inefficient farmer for every energy source. Another objective of this study was to calculate GHG emissions for efficient and inefficient units of watermelon production. In other words, the main aim of this research was to determine energy optimization affected by DEA in GHG emission reduction.

2. Materials and methods

2.1. Sampling design

This study follows our previous study which was conducted on modeling and sensitivity analysis of energy use and GHG emissions of watermelon production using artificial neural networks (Nabavi-Pelesaraei et al., 2016). Accordingly, data used in this study were obtained from 120 watermelon farms from 4 villages in Guilan province of Iran in 2012–2013 crop years. The location of the studied area is shown in Fig 1.

2.2. Energy equivalents of inputs and output

In Guilan province of Iran, there are eight energy inputs for watermelon production including: human labor, machinery, diesel fuel, chemical fertilizers, farmyard manure, biocides, electricity and seed. The results summary of energy calculation are illustrated in Table 1. Based on results, the total energy consumption and watermelon yield were about 40,229 MJ ha^{-1} (with the standard deviation of 16912.48) and 27,349 kg ha^{-1} (standard deviation of 13724.20), respectively. Also, the high rate of energy consumption belonged to nitrogen with 28003.70 MJ ha^{-1}; followed by diesel fuel with 3463.40 MJ ha^{-1} and electricity with 3077.33 MJ ha^{-1}.

2.3. DEA approach

DEA is known as a mathematical procedure that uses a linear programing technique to assess the efficiencies of decision-making units (DMU). A non-parametric piecewise frontier, which owns the optimal efficiency over the datasets, is composed of DMUs and is constructed by DEA for a comparative efficiency measurement. Those DMUs that are located at the efficiency frontier are efficient DMUs. These DMUs own the best efficiency among all DMUs and have their maximum outputs generated among all DMUs by taking the minimum level of inputs (Lee and Lee, 2009). There are two kinds of DEA models included: CCR and BCC models (Charnes et al., 1978). The CCR model is built on the assumption of constant returns to scale (CRS) of activities, but the BCC model is built on the assumption of variable returns to scale (VRS) of activities. Efficiency by DEA is defined in three different forms: overall technical efficiency (TE_{CCR}), pure technical efficiency (TE_{BCC}) and scale efficiency (Heidari et al., 2012).